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Review

Adapting Agricultural Production Systems to Climate Change—What's the Use of Models?

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Abstract: Climate change poses a challenge to agricultural production and its impacts vary depending on regional focus and on the type of production system. To avoid production losses and make use of emerging potentials, adaptations in agricultural management will inevitably be required. Adaptation responses can broadly be distinguished into (1) short-term incremental responses that farmers often choose autonomously in response to observed changes and based on local knowledge and experiences, and (2) long-term transformative responses that require strategic planning, and which are usually implemented at a larger spatial scale. Models can be used to support decision making at both response levels; thereby, different features of models prove more or less valuable depending on the type of adaptation response. This paper presents a systematic literature review on the state-of-the-art in modelling for adaptation planning in agricultural production systems, investigating the question of which model types can be distinguished and how these types differ in the way they support decision making in agricultural adaptation planning. Five types of models are distinguished: (1) empirical crop models; (2) regional suitability models; (3) biophysical models; (4) meta-models; and (5) decision models. The potential and limitations of these model types for providing decision-support to short- and long-term adaptation planning are discussed. The risk of maladaptation—adaptation that implies negative consequences either in the long term or in a wider context—is identified as a key challenge of adaptation planning that needs more attention. Maladaptation is not only a risk of decision making in the face of incomplete knowledge of future climate impacts on the agricultural production system; but it can also be a threat if the connectedness of the agroecosystem is not sufficiently acknowledged when management adaptations are implemented. Future research supporting climate change adaptation efforts should thus be based on integrated assessments of risk and vulnerabilities (considering climate variability and uncertainty). To secure adaptation success in the long term, frameworks for monitoring management adaptations and their consequences should be institutionalised.

Keywords: agricultural modelling; decision-support; adaptation planning; maladaptation risk

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1. Introduction

1.1. Climate Impacts and Adaptation in Agricultural Production Systems

Climate, with its regional and temporal variability, is a major determinant of agricultural production. All agricultural production is related to the performance of (cultivated) species, which are bound to particular environmental conditions. As climatic conditions change, also production conditions are likely to change with possible positive or negative implications on agricultural production [1–3]. While agriculture provides humanity with essential goods (i.e., food, fodder, fiber or biofuel), agricultural management also affects important ecosystem services such as the provision of clean water or soil protection [4]. It is important to anticipate future changes in the agroecosystem to be able to respond adequately and maintain its functionality with regard to multiple ecosystem services. If climate change impacts on agroecosystem functioning are known, measures can be planned to adapt agricultural management in order to prevent the negative impacts of climate change and to exploit new, emerging potentials [5,6].

The need for "urgent action to combat climate change and its impacts" has recently been called for in the 13th of the 17 UN Sustainable Development Goals that were officially ratified in September 2015 and should be achieved over the next 15 years. This goal places particular emphasis on strengthening resilience and adaptive capacity to climate risks and natural disasters. In the context of adaptation in agroecosystems, Goal 13 is linked to the second goal, which is to "end hunger, achieve food security and improved nutrition and promote sustainable agriculture". One of the targets to achieve this goal, which is clearly linked with the 13th Goal, is to "ensure sustainable food production systems and implement resilient agricultural practices that increase productivity and production, help maintain ecosystems, strengthen the capacity for adaptation to climate change, extreme weather, drought, flooding and other disasters, and progressively improve land and soil quality". The desire to maintain and improve productivity, while promoting synergies with other functions of the socio-ecological agroecosystem, is thus clearly articulated and agreed upon in an international arena.

While being high on international and national agendas, climate change adaptation is clearly also in the interest of individual farmers or farming cooperatives that rely on the revenue generated from agricultural production. On farm properties, changes in land use and management will be required in order to adapt food production systems to changes in climate and other emerging pressures.

1.2. Two Types of Adaptation Responses

Even though different authors make distinctions based on different criteria, two types of adaptation responses can broadly be distinguished [7–10]:

- Type A—the short-term, incremental responses that are often chosen autonomously in response to observed changes and based on local knowledge and experience, and
- Type B—the long-term, transformative responses that require strategic planning, which is usually implemented at a larger spatial scale (regional, national or international).

Both types of adaptation responses are essential for reducing risks from weather and climate extremes (high agreement, robust evidence, [11]). Type A responses help to improve management efficiency within existing technological, governance, and value systems, whereas Type B responses may involve alteration of the fundamental attributes of those systems.

The realised ratio of these two types of responses depends on the balance between climate impact and the adaptive capacity of the affected socio-ecological system. If climate impacts are relatively mild, not pushing the existing production system beyond its feasibility boundaries, and if adaptive capacity is high, adaptation can be facilitated by Type A responses. If climate impacts are more extreme, and the scope for Type A responses is narrow (e.g., due to limited access to resources and technologies), Type B responses can quickly become indispensable.

1.2.1. Type A Adaptation: Short-Term, Incremental, Autonomous, Reactive, and Localised

Moderate impacts of climate change occurring over a longer time period can usually be addressed successfully with Type A responses without a great need for strategic planning or coordination. Type A adaptation responses can include changes in sowing dates, cultivar or crop choice, and the adaptation of water, nutrient, residue and canopy management. By shifting the sowing date, farmers can make use of the extended growing season associated with climate warming. Also, sowing date shifts provide the possibility of avoiding crop exposure to particular climatic stresses such as heat or drought during sensitive phenological stages. If the growing season is extended, double-cropping or even triple-cropping may become suitable options for increasing the land productivity under climate change (e.g., [12]). Shifting to cultivars or crops with increased tolerance to the most dominate stress factors can help to mitigate climate risks.

In livestock systems, adaptation can involve flexible herd management, stable construction and indoor climate control systems, choosing alternative livestock breeds or species, dietary choices, and innovative pest management (e.g., [13]).

Diversification of farm management is also one possibility for adaptation that is often suggested, especially under conditions of high climatic variability or high uncertainty (e.g., [14,15]). In a diversified production system with different crops, cultivars and staggered planting dates, stability is increased by compensating possible yield losses in response to a particular climate incidence by other yields that are less affected by this incidence or that may even benefit from it.

1.2.2. Type B Adaptation: Long-Term, Transformative, Strategic, Anticipatory, and Large-Scale (Regional, National or Even International)

Where climate change impacts exceed a certain threshold that can no longer be alleviated by Type A responses, more fundamental transformative changes may be required [16]. These can include spatial shifts in production zones, structural changes in production systems implying substantial shifts in farming activities, or breeding of new crops and cultivars. For farmers, this may imply investment in the infrastructure required for the new production systems. At the public levels, incentive systems may have to be adapted to help steer the direction of transformative adaptation and support farmers' adaptation efforts. Agro-industries need to plan ahead in their development of new technologies and the breeding of new cultivars. Examples of specific breeding goals include resistance to high temperatures that cause spikelet sterility and altered phenology so that cropping systems can be redistributed as climate conditions for agroecological zones shift [17,18]. Further breeding goals for adaptation can include tolerances to flooding, drought or increased salinity as well as water- and nutrient-use-efficiencies. Also, the ability of crops to adapt their phenotype to changing environmental conditions (phenotypic plasticity) can be considered a desirable trait when breeding for climate-resilient crops [19,20].

Transformative adaptation—since it requires greater foresight and coordination—would rely on appropriate intuition and mechanisms to promote the implementation of sustainable adaptation strategies. Transformative changes require a long-term planning vision and involve a series of challenges, risks, and benefits [9]. The fact that transformative decision making involves greater uncertainty than that associated with incremental adaptation presents a particular challenge in this context [21]. Risk management and robust decision making will thus represent the core features of transformation [5].

Models can provide decision-support for adaptation planning in agriculture in three major ways: (1) they can foster the understanding of physical and socio-economic systems and their scientific theories, helping to identify major drivers and limitations; (2) the predictive capabilities of modelling tools can be utilised to anticipate future climatic risks; and (3) models may be applied in explorative modes to test and eventually rank particular options of climate adaptation according to their environmental and socio-economic impacts. Since the 1980s, model-based tools have been applied for climate impacts assessments in agriculture ([22,23]). The level of integration over different responses, pressures, and systems was initially low, but increased with method development over the following decades [24]. Reidsma et al. [25] call for further improvements in model integration—especially linking biophysical and economic models—to better address the challenges of agricultural adaptation to climate change. Harrison et al. [26] highlight the need for cross-sectoral climate impact assessments to avoid misinterpretation of impacts and consequent poor decisions about climate adaptation.

1.3. The Risk of Maladaptation in Agriculture

If adaptation decisions are taken under the wrong assumptions, they may lead to undesirable outcomes. Barnett and O'Neill [27] define this as "maladaptation", i.e., as the result of an action taken ostensibly to avoid or reduce vulnerability to climate change that impacts adversely on, or increases the vulnerability of other systems, sectors or social groups. Maladaptation can occur if short-term benefits outweigh longer-term (social, economic or environmental) costs, or if possible negative external effects of management adaptation are simply not taken into consideration, because they do not impact the welfare of the decision maker. For example, if a desalination plant or irrigation infrastructure is built to adapt to increasing water scarcity, possible maladaptive outcomes could be increased emissions by building and operating the infrastructure, increasing water costs or negative impacts on aquatic biodiversity [28]. Such negative externalities can only be accounted for in an integrated assessment of adaptation strategies (see also Reidsma et al., [25]). Once a choice has been made for an adaptation option, it can reduce the portfolio of adaptation options for the future—i.e., path dependencies may occur—either because the selected adaptation option is connected with a high expenditure that constrains financial resources for further options or because the choice of the adaptation option leads to an over-exploitation of natural resources (e.g., [29,30]). Maladaptation at the policy level can limit the producers' own independent moves towards adaptation if the wrong incentives are created [31].

One risk of maladaptive decision-support thus lies in the under- or misrepresentation of possible negative externalities if underlying models neglect important system linkages. Another risk of applying models for supporting decisions in adaptation planning lies in the potentially large uncertainties in model estimates originating from (1) context uncertainty, (2) input uncertainty, (3) model structure uncertainty, (4) parameter uncertainty, and (5) modelling technical uncertainty [10,32,33]. Uncertainties in model estimates cascade down from pathways of radiative forcing to climate models, downscaled climate projections, impact estimates and finally to recommendations for appropriate adaptation responses [34].

It is thus evident that to avoid maladaptive decision making, model uncertainties have to be treated thoroughly and findings should be incorporated into integrated assessments of possible negative externalities.

2. Systematic Literature Review

To gain a systematic overview of the "state-of-the-art" of model applications dealing with climate change adaptation in agriculture, a literature survey was conducted using SCOPUS, searching for the terms "modelling", "climate change", "adaptation" and "agriculture" within titles, abstracts and keywords. Subject areas included in the search were "Agricultural and Biological Sciences" (64), "Computer Science" (4), "Earth and Planetary Sciences" (60), "Environmental Science" (147), and "Social Sciences" (19). Only journal articles in English, French and German language were considered. The survey conducted on 25 September 2017 resulted in a selection of 210 papers. 169 of these papers were published in the years between 2013 and 2017, which shows that the subject of the review is at the centre of current scientific debate. After a first review of these 210 articles, 51 papers were excluded because they did not report on modelling case studies in the context of climate change adaptation in agriculture, but used methods other than modelling (e.g., interview studies) or were rather general reviews, editorials, project descriptions, opinion papers or dissertations. The 159 papers selected for this review are not considered inclusive, but are assumed to provide a representative overview of modelling case studies conducted on climate change impact assessments and adaptation in agriculture up to the time when this review was conducted. The review of the remaining 88 papers is summarised in the Supplementary Material. The studies were analysed in terms of the model approaches applied, the impact indicators considered and adaptation options tested. Based on this analysis, the following five model approaches can be distinguished:

- Empirical models
- Regional suitability models
- Biophysical models
- Meta-models
- Decision models

2.1. Empirical Crop Models

Empirical crop models estimate climate-yield relationships based on empirical time series and/or panel datasets of spatial and temporal variation in yield and climate variables. Such models do not usually explicitly account for the possibilities of adaptation. However, since autonomous adaptation is continuously progressing, it would be implicitly accounted for if models are based on long-time series of data. The study of Gornott and Wechsung [35] applies this approach, stating that autonomous adaptation measures taken by farmers such as shifts in sowing dates and choice of cultivars are implicitly accounted for in the empirical model. Due to its limited ability to model possible adaptation responses, the empirical crop model approach is mostly applied for agricultural climate impact assessments (e.g., [1,36]). An exception included in this review is the study by Jiang and Koo [37], which applies an empirical crop model that integrates not only climatic predictor variables, but also management-related input variables (i.e., fertilizer prices and crop prices lagged one year to represent producer-expected output prices). Similarly, Hobbs et al. [38] developed and applied statistical models of forest biomass production given different planting designs.

A general advantage of the empirical model approach is that it can be applied to fit yield response functions to available data, even if that data is scarce or only available in an aggregated form (e.g., monthly climate data). It can be applied analytically for identifying region-specific main climatic drivers of yield and yield changes. Predictions of validated models can be considered valid within the range of data that was used for fitting the models. However, their ability to provide correct predictions beyond observed conditions may be hampered by the fact that causal relationships hypothesised based on observed data may not represent the process-relationships beyond observations.

2.2. Regional Suitability Models

Regional land or climate suitability approaches are usually applied to quantify biophysical land use potential under current and future climatic conditions at a regional scale [39,40]. For example, Pelizaro et al. [40] apply a multi-criteria evaluation approach based on soil, landscape and climate criteria to assess agricultural land suitability. Brown et al. [39] apply a rule-based evaluation of agricultural potential based on accumulated temperature and maximum soil moisture deficit. These two approaches utilise expert judgement and/or empirical field evidence to define responses to the different evaluation criteria. Examples of fully empirical regional suitability approaches, as they are commonly applied for modelling potential distributions of natural species, can be found in the studies of Bennett et al. [41] and Malviya et al. [42]. In contrast to empirical crop models, which aim at predicting yields, suitability approaches estimate the probability of occurrence of a particular species. Malviya et al. [42] apply a species distribution model for evaluating the potential of *Simarouba glauca* under climate change. Results of their study may suggest where the cultivation of this species can be a suitable adaptation option. Bennett et al. [41] apply a climate niche modelling approach (DOMAIN by Carpenter et al., [43]) for investigating natural adaptation of native pasture species in Western Australia. Their results help to prioritise novel pasture species for use in water-limited agriculture. Similar to the empirical crop model approach, land suitability evaluation approaches usually do not allow for testing explicit management adaptations. However, since the approach quantifies land potential for particular crops, it can highlight regions of increasing or decreasing suitability for particular land use types, indicating where shifts in cultivation zones can be considered as suitable adaptation options. Information for adaptation planning can also be derived based on this approach if changes in particular limiting factors can be identified, thus steering the identification of suitable adaptation measures. For example, Zhang et al. [44] and Perdinan et al. [45] provided an indicator-based evaluation of regional drought hazards under current climate and future climate.

Besides regional quantifications of abiotic limitations, the regional suitability approach can also be applied to estimate the potential distribution of pests and invasive species under current and future climatic conditions (e.g., [46,47]).

2.3. Biophysical Models

The vast majority of case studies selected for this review applied process-based biophysical models (57 references). Biophysical models simulate biophysical processes such as plant growth, nutrient and carbon dynamics, water cycling and flood inundation based on mechanistic process understanding, which is mathematically formalised.

The most frequently applied models are CropSyst (Cropping Systems Simulation Model [48]; 7 studies), CERES (Crop Environment REsource Synthesis [49]; 8 studies), SWAT/SWIM (Soil Water Assessment Tool/ Soil and Water Integrated Model [50]; 12 studies), CROPWAT/AquaCrop (the FAO crop model [51]; 10 studies), APSIM (Agricultural Production Systems sIMulator [52]; 11 studies), DSSAT (Decision Support System for Agrotechnology Transfer [53]; 9 studies), EPIC (Erosion Productivity Impact Calculator [54]; 4 studies), STICS (Simulateur mulTIdiscplinaire pour les Cultures Standard [55]; 4 studies), LPJmL (Lund-Potsdam-Jena managed Land model [56]; 4 studies), and MIKE (Modeling System for Rivers and Channels [57]; 2 studies). These biophysical models differ in terms of spatial scale, levels of integration and complexity. While APSIM, CropSyst, CERES, DSSAT, CROPWAT/AquaCrop, STICS and EPIC are designed for simulating biophysical processes at the plot level, LPJmL, SWAT/SWIM and MIKE are spatially distributed models, usually applied at regional or even global scale. The plot-scale models mostly focus on representing crop growth processes with different degrees of complexity. The more simplistic approach of CROPWAT/AquaCrop simulate water limitations to potential crop yields. STICS, CERES and the crop modelling suite DSSAT (which integrates CERES amongst other crop models), simulate crop responses to the dynamics of soil water, nutrients and soil carbon. EPIC and CropSyst simulate crop growth processes at a similar level of complexity, but also integrate the effects of climate and management on soil erosion. A very detailed representation of crop growth processes is integrated in the model APSIM, which differentiates between plant components (leaf, stem, head, and root) and also allows for simulating competition between species in crop mixtures.

Since the models incorporate explicit process descriptions, they allow for testing the effects of climate and management changes and interactions thereof, thus providing an excellent basis for simulating not only the impacts of climate change on various agroecosystem functions, but also for testing adaptation options (e.g., irrigation as an obvious measure to prevent drought stress).

2.4. Meta-Models

With respect to meta-models we summarise approaches that integrate information collected from different sources (e.g., model results derived from complex mechanistic models, collections of databases, literature studies) to provide a broad basis for multi-criteria decision making. Life-cycle assessment (LCA) approaches, for example, utilise information from a wide range of exemplary impact studies to provide a broad basis for prioritising products or production pathways in terms of their overall impacts. Examples of such studies included in this review are Renaud-Gentie et al. [58] and Tendall and Gaillard [59]. A literature-based meta-analysis to provide a semi-quantitative overview of current and possible future climate-related risks to agriculture is presented in Schaap et al. [60]. Audsley et al. [61] apply the neural network approach to derive meta-models from outputs of previously developed very complex and integrated models. The benefit of applying the meta-model instead of the complex integrated model is the reduced run-time, which increases the feasibility of the model to be applied for explorative analyses. By testing many alternative scenarios on-the-fly within learning sessions, decision makers can gain understanding of the system responses to environmental and management changes, which can help them in finding the most desirable management alternative. The strength of these meta-model approaches is their integrative capacity. They can provide a broad base for decision making in terms of climate change adaptation, since they consider a large variety of impacts (not only on the agricultural sector). Thus, they can be applied to identify trade-offs and synergies in management adaptations beyond the local agroecosystem (e.g., synergies between adaptation and mitigation objectives). The integrative capacity brings with it also the possibility to foster social learning and integrated system thinking amongst stakeholders and decision makers.

2.5. Decision Models

The second-largest proportion of case studies analysed in this review apply models which consider the decisions that farmers take in response to changing climatic, economic or social conditions. Since decisions are explicitly incorporated in these models, these models are termed decision models here. The majority of these models simulate farmers' adaptation decisions in response to biophysical and economic drivers. These models are also termed bio-economic models. They are usually based on a coupling between a process-based biophysical model or an empirical production model and an economic farm optimization model. Exceptions from these bio-economic models are the studies of Berry et al. [62] and Yegbemey et al. [63]. They focus on farmers' adaptive behavior in response to socio-economic drivers. For example, Yegbemey et al. [63] apply a multi-variate probit model determining farmers' decisions to adapt to climate change given characteristics such as gender, level of education, experience in agriculture, household size, contact with extension services, access to credit, ownership or rights of cutting/selling/renting land. Berry et al. [62] apply hierarchical linear regression modelling to examine the extent to which, in a multivariate analysis, the use of adaptive practices was predictively associated with self-assessed health. Both these case studies aimed at quantifying what determines farmers' adaptive capacity (i.e., their ability to respond adequately to increasing climatic and/or economic variability).

3. The Value of Model-Based Information for Adaptation Planning

Depending on the level of the organisation at which adaptation decisions are taken (i.e., farm level or governmental) and depending on the planning horizon, different types of information are needed and different types of representations may be required to communicate findings effectively [64]. Based on the review of modelling studies of climate change adaptation in agriculture, we discuss the suitability of each model type for addressing different climate adaptation challenges. Information about future climate impacts on crop yields and, in particular, on changes in different climatic limitations can be the most valuable to inform long-term, transformative adaptation responses (Type B). For identifying breeding targets, for example, it is essential to know which crop traits would be beneficial under climate change, and in responding to particular climatic stresses. For the planning of adequate irrigation infrastructure, it is relevant to know how irrigation demands and water availability will be affected by future climate change. Results from climate impact assessments based on statistical crop models, process-based biophysical models and regional suitability models can provide such information.

While impact studies conducted using statistical, process-based or regional suitability approaches can provide a basis for discussing possible adaptation options, the effectiveness of adaptation options usually requires the use of process-based models. These models can either be applied to simulate the effects of adaptation options in scenario analyses or they can be integrated in simulation-optimization applications. Such studies allow for systematically exploring a predefined adaptation space in the search for optimum management scenarios with regard to particular adaptation goals. If multi-objective optimization is applied to identify all Pareto-optimal solutions, trade-offs and synergies can be explored systematically—providing relevant insights into system linkages in an agroecosystem. The benefits of this type of application for environmental management applications have been increasingly explored over the last few decades (e.g., [65–69]). The strong uptake of the approach by the community highlights its great potential. Particular optimum management scenarios can be considered as idealised targets for transformative adaptation pathways. As such, they can have strong potential for communicating feasible planning visions as a basis for normative discussions of planning objectives. However, given the potentially large model uncertainties, the target scenarios cannot be considered as static planning visions, but would have to be reassessed in regular decision cycles, following an adaptive management approach. One possibility for increasing the usability of target scenarios for planners and decision makers may lie in the combined use of optimum scenarios together with adaptation scenarios developed based on plausible storylines of developments. The potential of combining the benefits of both approaches (optimum achievement of targets and plausibility) could be explored in future studies. In general, the successful application of simulation-optimization techniques for solving real-world management problems remains a challenge due to a common lack of interaction between scientists and decision makers [70]. To overcome this challenge and link optimization applications more closely to real-world management problems, Wu et al. [71] recently proposed a framework for including stakeholder input at various stages in the optimization process. In this context, integrating model outputs into meta-model-type learning environments can help to visualise cross-benefits between management measures and facilitate communication and social learning in participatory planning. The higher the level of organisation dealing with adaptation planning, the greater the value of integrated large-scale assessments to support the coordination of policy measures (i.e., regulations, incentives) towards congruent outcomes. Approaches such as the Bayesian network approach can be useful to provide a broad integrated vulnerability assessments under climate change, while making prediction uncertainties explicit (see also Lynam et al., [72]). The large potential benefit of integrated assessment tools to help foster food security by providing a platform that brings modellers and stakeholders from different backgrounds together was also highlighted by Webber et al. [73].

While long-term transformative adaptation planning requires information about projected changes in relevant drivers (e.g., climatic, economic, demographic, political), decisions on short-term adaptation responses (Type-A) are mostly taken autonomously based on farmers' individual experiences and knowledge. Farmers with many years of experience managing their land and observing responses to their management and local climate variability may have no need for decision-support based on a generic computer model. However, knowledge, experience and understanding may not be uniform across the farming community and farmers may lack experience on measures which are new to a particular farm. Knowledge integration across the farming and the scientific community has the potential to improve the information base for adaptation for all, helping to make short-term adaptation responses more effective. Approaches such as the Bayesian network approach could be promising in this respect since they have shown great value for compiling best available data and knowledge and can easily be updated as new evidence becomes available. One example of such an application was recently provided by de Nijs et al. [74], who developed a Bayesian Belief Network incorporating climate projections, local environmental data, information from peer-reviewed literature and expert opinion to account for the adaptation benefits derived from Climate-Smart Agriculture activities in Malawi. The field of machine learning is evolving rapidly due to increasing availability of data and information (e.g., from social networks). The promising potential of emerging techniques for integrating adaptation knowledge could be explored in the future. Integrated into operational, web-based tools, such techniques can be very valuable to communicate relevant information to stakeholders. Besides providing information services, these platforms can also be designed to collect user feedback to improve the collective knowledge base. The ability to integrate user feedback could also help to track ongoing autonomous adaptation, thus collecting relevant information for anticipating emerging threats of maladaptation.

Furthermore, coordinated web-based knowledge platforms can provide the basis for building collaborative partnerships between scientists and decision makers, for sharing data, knowledge and experiences and thus for promoting the transition of scientific findings into decision making processes in adaptation planning (e.g., [75,76]).

4. Integration

The model applications reviewed here show a large variation in levels of integration in terms of the impacts considered (Table 1). Empirical crop models and regional suitability models focus on yield, and production potential only, while biophysical model approaches are applied to estimate impacts of climate and management changes on a much wider range of environmental objectives. Meta-models and decision models expand the scope of integrated objectives, with an increasing emphasis on economic objectives in decision models.

Table 1. Number of modelling studies simulating impacts on different objectives with each of the five identified model approaches.

	Empirical Crop Model	Regional Suitability Model	Biophysical Model	Meta-Model	Decision Model
yield/yield potential	7	9	62	10	25
water availability	0	0	28	6	4
water quality	0	0	10	1	1
flooding	0	0	4	1	0
soil loss	0	0	4	0	0
irrigation demand	0	2	15	4	4
wildlife habitat	0	0	2	1	0
pests, invasive species	0	2	0	0	0
soil carbon	0	0	1	0	0
peat cover	0	0	1	0	0
GHG emissions	0	0	0	1	3
livestock	0	0	3	2	1
food demand	0	0	0	0	2
farmers' profits	0	0	0	1	23
farmers' adaptation decisions	0	0	0	0	2
Total number of studies	7	13	94	16	30

Management adaptations were not modelled explicitly in all modelling studies reviewed here (Table 2). Statistical crop model approaches consider management adaptations only implicitly. In these modelling studies, the results of climate impact assessments are however discussed in context with adaptation options that may be advisable to alleviate the quantified impacts. Regional suitability approaches provide a basis for exploring the potential for adaptation through changes in production zones, which can be tested explicitly or simply discussed. Biophysical models provide a more straightforward basis for testing adaptation options, since management impacts are explicitly simulated with these approaches. This is also apparent from the large number of modelling studies of this type, exploring a wide range of management adaptations. Beyond these options, decision models integrating also economic and behavioral components allow for testing the effects of financing instruments and utilisation of forecasts.

Modelling tools for integrating large quantities of information either in the form of decision models, meta-models or integrated biophysical models have great potential to help reduce the risks of maladaptation (as predictive tools to anticipate impacts, as predictive and explorative tools to test the suitability of different adaptation options, or as explorative learning tools supporting social learning and participatory decision making).

Table 2. Number of modelling studies explicitly simulating different adaptation options with each of the five identified model approaches.

	Empirical Crop Model	Regional Suitability Model	Biophysical Model	Meta-Model	Decision Model
Sowing shift	0	0	18	0	1
Crop/cultivar choice	2	1	15	1	12
Irrigation	0	0	28	4	10
Fertilization	0	0	13	1	6
Soil management	0	0	4	0	1
Livestock breed	0	0	1	0	3
Grazing intensity	0	0	0	0	2
Water harvesting/storage	0	0	5	1	1
Re-wetting	0	0	1	0	0
Wasterwater treatment	0	0	1	0	0
Buffer zones	0	0	1	0	0
Relocation of cultivation areas	0	1	9	2	5
Availability of forecasts	0	0	0	0	3
Financing/policy instruments	0	0	0	4	5
Total number of studies	7	13	94	16	30

5. Uncertainties

Most of the modelling studies reviewed here did account for uncertainties in one way or another (77% of the reviewed studies), showing that the importance of handling uncertainty is generally well acknowledged within the research community. The uncertainty source that is most commonly represented is climate projection uncertainty (63.5% of the studies considered between 2 and 24 climate scenarios). The climate scenarios were based on different combinations of emission pathways and global/regional climate model simulations and where only a few scenarios were used to keep the computational effort to a minimum, these scenarios were selected to represent extremes. An alternative approach to accounting for climate projection uncertainties is to explore impact model sensitivities to changes in radiation, precipitation, temperature and CO_2 changes (12.5% of the reviewed studies). This approach is most frequently applied in combination with decision models (7% of all studies and 30% of the decision model applications reviewed here). Some studies, particularly decision model applications also accounted for other uncertainty sources such as change in land use or price changes. These assumptions were usually based on storylines of coherent developments of socio-economic drivers.

Of the remaining 23% of studies without explicit consideration of uncertainties, many used historical climate data for their investigations of climate impacts and adaptation possibilities; e.g., focusing on selected extreme years in observations. Only a few studies (10%) estimated climate change impacts on agriculture based on a single climate projection and impact model specification. While uncertainties in impact estimates are usually well represented and discussed in the reviewed studies, the robustness of adaptation measures is rarely evaluated.

6. Summary and Conclusions

In this review paper, the use of current models to support climate change adaptation in agriculture was explored. Based on a systematic literature review, five different modelling approaches were distinguished: (1) empirical crop models, (2) regional suitability models, (3) biophysical models, (4) meta-models, and (5) decision models. The five approaches differ in terms of their applicability for decision-support in short-term and long-term adaptation planning. For transformative adaptation planning, which requires longer planning horizons, the main value of model-based tools lies in their ability to predict climate change impacts and to explore possible adaptation measures. While empirical crop model approaches and regional suitability models are mostly applied to estimate climate change impacts on yield potentials at local and regional levels, biophysical models and meta-models show great strength in assessing impacts on multiple objectives. Adaptation possibilities are mostly explored using biophysical models, meta-models and decision models. Integrated simulation-optimization applications of biophysical models show particularly significant potential for supporting decisions in transformative adaptation planning (e.g., optimum breeding targets, farm input schedules and allocations of productions zones can be identified demonstrating the idealised scope for adaptation). Future research should further explore the use of optimization results as a basis for normative discussions of planning objectives and suitable adaptation pathways.

For short-term, reactive adaptation responses, statistical and biophysical models are less useful, but meta-models and decision models can be valuable to help build system resilience, by making synthesised information on socio-ecological system linkages available. Both these model approaches have great potential for being used as explorative learning tools, which should be explored in future research and participatory applications. Also, the potential of emerging machine-learning techniques for integrating adaptation knowledge should be explored.

Both short-term and long-term adaptation responses bear the risk of maladaptation (e.g., if adaptation measures imply disproportionally high environmental, economic or social costs). To prevent such maladaptation, integrated assessments of climate and management changes and the consideration of uncertainties are key elements for model-based decision-support. Integrated assessments allow for identifying unintended effects/costs that would be neglected in studies with a singular focus on agricultural productivity. If uncertainties in model outputs are quantified, robust adaptation responses can be identified, preventing the implementation of adaptation responses that fail to meet their objectives. It also has to be acknowledged that not all risks are predictable and not all uncertainties affecting decision making can be quantified and anticipated. Therefore, adaptive management cycles should be institutionalised, within which adaptation behaviour/autonomous adaptation, consequences of adaptation responses and changes in impacts are continuously monitored. Predictive modelling tools should be continuously improved on the basis of this data and applied to anticipate the impact of future climate change and adaptive management changes and thus help reduce emerging risks to other functions and sectors.

Supplementary Materials: The following are available online at http://www.mdpi.com/2077-0472/7/10/86/s1.

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References

1. Lobell, D.B.; Burke, M.B.; Tebaldi, C.; Mastrandrea, M.D.; Falcon, W.P.; Naylor, R.L. Prioritizing climate change adaptation needs for food security in 2030. *Science* **2008**, *319*, 607–610. [CrossRef] [PubMed]
2. Olesen, J.E.; Bindi, M. Consequences of climate change for European agricultural productivity, land use and policy. *Eur. J. Agron.* **2002**, *16*, 239–262. [CrossRef]
3. Rosenzweig, C.; Parry, M.L. Potential impact of climate changes on world food supply. *Nature* **1994**, *367*, 133–138. [CrossRef]
4. Foley, J.A.; Ramankutty, N.; Brauman, K.A.; Cassidy, E.S.; Gerber, J.S.; Johnston, M.; Mueller, N.D.; O'Connell, C.; Ray, D.K.; West, P.C.; et al. Solutions for a cultivated planet. *Nature* **2011**, *478*, 337–342. [CrossRef] [PubMed]
5. Howden, S.M.; Soussana, J.-F.; Tubiello, F.N.; Chhetri, N.; Dunlop, M.; Meinke, H. Adapting agriculture to climate change. *PNAS* **2007**, *104*, 19691–19696. [CrossRef] [PubMed]
6. Schiermeier, Q. Quest for climate-proof farms. *Nature* **2015**, *523*, 396–397. [CrossRef] [PubMed]
7. O'Brien, K. Global environmental change II: From adaptation to deliberate transformation. *Prog. Hum. Geogr.* **2012**, *36*, 667–676. [CrossRef]
8. Park, S.E.; Marshall, N.A.; Jakku, E.; Dowd, A.M.; Howden, S.M.; Mendham, E.; Fleming, A. Informing adaptation responses to climate change through theories of transformation. *Glob. Environ. Chang.* **2012**, *22*, 115–126. [CrossRef]

9. Rickards, L.; Howden, S.M. Transformational adaptation: Agriculture and climate change. *Crop Pasture Sci.* **2012**, *63*, 240–250. [CrossRef]
10. Walker, W.; Haasnoot, M.; Kwakkel, J. Adapt or Perish: A Review of Planning Approaches for Adaptation under Deep Uncertainty. *Sustainability* **2013**, *5*, 955–979. [CrossRef]
11. O'Brien, K.; Pelling, M.; Patwardhan, A.; Hallegatte, S.; Maskrey, A.; Oki, T.; Oswald-Spring, Ú.; Wilbanks, T.; Yanda, P.Z.; Giupponi, C.; et al. *Toward a Sustainable and Resilient Future, Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation: Special Report of the Intergovernmental Panel on Climate Change*; Cambridge University Press: Cambridge, UK, 2012; pp. 437–486.
12. Liang, Z.; Gu, T.; Tian, Z.; Zhong, H.; Liang, Y. Agro-climatic adaptation of cropping systems under climate change in Shanghai. *Front. Earth Sci.* **2015**, *9*, 487–496. [CrossRef]
13. Joyce, L.A.; Briske, D.D.; Brown, J.R.; Polley, H.W.; McCarl, B.A.; Bailey, D.W. Climate change and North American rangelands: Assessment of mitigation and adaptation strategies. *Rangel. Ecol. Manag.* **2013**, *66*, 512–528. [CrossRef]
14. Fraser, E.D.; Mabee, W.; Figge, F. A framework for assessing the vulnerability of food systems to future shocks. *Futures* **2005**, *37*, 465–479. [CrossRef]
15. Reidsma, P.; Ewert, F. Regional farm diversity can reduce vulnerability of food production to climate change. *Ecol. Soc.* **2008**, *13*, 38. [CrossRef]
16. Roggema, R.; Vermeend, T.; van den Dobbelsteen, A. Incremental change, transition or transformation? Optimising change pathways for climate adaptation in spatial planning. *Sustainability* **2012**, *4*, 2525–2549. [CrossRef]
17. Chenu, K.; Porter, J.R.; Martre, P.; Basso, B.; Chapman, S.C.; Ewert, F.; Bindi, M.; Asseng, S. Contribution of Crop Models to Adaptation in Wheat. *Trends Plant Sci.* **2017**, *22*, 472–490. [CrossRef] [PubMed]
18. Rosenzweig, C.; Hillel, D. Conclusion: Agricultural Solutions for Climate Change at Global and Regional Scales. In *Handbook of Climate Change and Agroecosystems—Global and Regional Aspects and Implications*; Hillel, D., Rosenzweig, C., Eds.; Imperial College Press: London, UK, 2013; pp. 281–292.
19. Bloomfield, J.A.; Rose, T.J.; King, G.J. Sustainable harvest: Managing plasticity for resilient crops. *Plant Biotechnol. J.* **2014**, *12*, 517–533. [CrossRef] [PubMed]
20. Nicotra, A.B.; Atkin, O.K.; Bonser, S.P.; Davidson, A.M.; Finnegan, E.J.; Mathesius, U.; Poot, P.; Purugganan, M.D.; Richards, C.L.; Valladares, F.; et al. Plant phenotypic plasticity in a changing climate. *Trends Plant Sci.* **2010**, *15*, 684–692. [CrossRef] [PubMed]
21. Leclère, D.; Havlík, P.; Fuss, S.; Schmid, E.; Mosnier, A.; Walsh, B.; Valin, H.; Herrero, M.; Khabarov, N.; Obersteiner, M. Climate change induced transformations of agricultural systems: Insights from a global model. *Environ. Res. Lett.* **2014**, *9*. [CrossRef]
22. Hoogenboom, G. Contribution of agrometeorology to the simulation of crop production and its applications. *Agric. For. Meteorol.* **2000**, *103*, 137–157. [CrossRef]
23. Parry, M. *Climate Change and World Agriculture*; Earthscan Publications Limited: London, UK, 1990; p. 157.
24. Holzworth, D.P.; Snow, V.; Janssen, S.; Athanasiadis, I.N.; Donatelli, M.; Hoogenboom, G.; White, J.W.; Thorburn, P. Agricultural production systems modelling and software: Current status and future prospects. *Environ. Model. Softw.* **2015**, *72*, 276–286. [CrossRef]
25. Reidsma, P.; Wolf, J.; Kanellopoulos, A.; Schaap, B.F.; Mandryk, M.; Verhagen, J.; Van Ittersum, M.K. Climate change impact and adaptation research requires integrated assessment and farming systems analysis: A case study in the Netherlands. *Environ. Res. Lett.* **2015**, *10*. [CrossRef]
26. Harrison, P.A.; Dunford, R.W.; Holman, I.P.; Rounsevell, M.D.A. Climate change impact modelling needs to include cross-sectoral interactions. *Nat. Clim. Chang.* **2016**, *6*, 885–890. [CrossRef]
27. Barnett, J.; O'Neill, S. Maladaptation. *Glob. Environ. Chang.* **2010**, *20*, 211–213. [CrossRef]
28. Barnett, J.; O'Neill, S.J. Minimising the risk of maladaptation: A framework for analysis. In *Climate Adaptation Futures*; Palutikof, J., Boulter, S.L., Ash, A.J., Smith, M.S., Parry, M., Waschka, M., Guitart, D., Eds.; Wiley & Sons: Chichester, UK, 2013; pp. 87–93.
29. Haydu, J. Reversals of fortune: Path dependency, problem solving, and temporal cases. *Theory Soc.* **2010**, *39*, 25–48. [CrossRef]
30. Yesuf, M.; Bluffstone, R.A. Poverty, Risk Aversion, and Path Dependence in Low-Income Countries: Experimental Evidence from Ethiopia. *Am. J. Agric. Econ.* **2009**, *91*, 1022–1037. [CrossRef]

31. Stupak, N. Adaptation of Russian agriculture to climatic variability: The role of federal and provincial policies. *Environ. Sci. Policy* **2017**, *68*, 10–19. [CrossRef]
32. Holzkämper, A.; Calanca, P.; Honti, M.; Fuhrer, J. Projecting climate change impacts on grain maize based on three different crop model approaches. *Agric. For. Meteorol.* **2015**, *214–215*, 219–230. [CrossRef]
33. Walker, W.E.; Harremoes, P.; Rotmans, J.; Van der Sluijs, J.P.; Van Asselt, M.B.A.; Janssen, P.; Krayer von Krauss, M.P. Defining Uncertainty—A conceptual basis for uncertainty management in model-based decision support. *Integr. Assess.* **2003**, *4*, 5–17. [CrossRef]
34. Wilby, R.L.; Dessai, S. Robust adaptation to climate change. *Weather* **2010**, *65*, 180–185. [CrossRef]
35. Gornott, C.; Wechsung, F. Level normalized modeling approach of yield volatility for winter wheat and silage maize on different scales within Germany. *J. Kulturpflanzen* **2015**, *67*, 205–223.
36. Lobell, D.B.; Field, C.B.; Cahill, K.N.; Bonfils, C. Impacts of future climate change on California perennial crop yields: Model projections with climate and crop uncertainties. *Agric. For. Meteorol.* **2006**, *141*, 208–218. [CrossRef]
37. Jiang, Y.; Koo, W.W. Estimating the local effect of weather on field crop production with unobserved producer behavior: A bioeconomic modeling framework. *Environ. Econ. Policy Stud.* **2014**, *16*, 279–302. [CrossRef]
38. Hobbs, T.J.; Neumann, C.R.; Meyer, W.S.; Moon, T.; Bryan, B.A. Models of reforestation productivity and carbon sequestration for land use and climate change adaptation planning in South Australia. *J. Environ. Manag.* **2016**, *181*, 279–288. [CrossRef] [PubMed]
39. Brown, I.; Towers, W.; Rivington, M.; Black, H.I.J. Influence of climate change on agricultural land-use potential: Adapting and updating the land capability system for Scotland. *Clim. Res.* **2008**, *37*, 43–57. [CrossRef]
40. Pelizaro, C.; Benke, K.; Sposito, V. A Modelling Framework for Optimisation of Commodity Production by Minimising the Impact of Climate Change. *Appl. Spat. Anal. Policy* **2011**, *4*, 201–222. [CrossRef]
41. Bennett, R.G.; Ryan, M.H.; Colmer, T.D.; Real, D. Prioritisation of novel pasture species for use in water-limited agriculture: A case study of Cullen in the Western Australian wheatbelt. *Genet. Resour. Crop Evol.* **2011**, *58*, 83–100. [CrossRef]
42. Malviya, S.; Priyanka, N.; Irfan-Ullah, M.; Davande, S.; Joshi, P.K. Distribution potential of *Simarouba glauca* under climate change—Strategizing rural livelihood adaptation. *Int. J. Geoinf.* **2013**, *9*, 31–37.
43. Carpenter, G.G.; Gillison, A.N.; Winter, J. DOMAIN: A flexible modelling procedure for mapping potential distributions of plants and animals. *Biodivers. Conserv.* **1993**, *2*, 667–680. [CrossRef]
44. Zhang, Q.; Zhang, J. Drought hazard assessment in typical corn cultivated areas of China at present and potential climate change. *Nat. Hazards* **2016**, *81*, 1323–1331. [CrossRef]
45. Perdinan; Adi, R.F.; Arini, E.Y. Regional Analysis of Prone Drought Areas under Future Climate Change Scenarios: Case Study Agropolitan of Malang District. *IOP Conf. Ser. Earth Environ. Sci.* **2007**, *58*. [CrossRef]
46. Biber-Freudenberger, L.; Ziemacki, J.; Tonnang, E.Z.; Borgemeister, C. Future risks of pest species under changing climatic conditions. *PLoS ONE* **2016**, *11*. [CrossRef]
47. Chapman, D.S.; Scalone, R.; Štefanić, E.; Bullock, J.M. Mechanistic species distribution modeling reveals a niche shift during invasion. *Ecology* **2017**, *98*, 1671–1680. [CrossRef] [PubMed]
48. Stöckle, C.O.; Donatelli, M.; Nelson, R. CropSyst, a cropping systems simulation model. *Eur. J. Agron.* **2003**, *18*, 289–307. [CrossRef]
49. Hoogenboom, G.; Jones, J.W.; Wilkens, P.W.; Batchelor, W.D.; Bowen, W.T.; Hunt, L.A.; Pickering, N.B.; Singh, U.; Godwin, D.C.; Baer, B.; et al. (Eds.) *Decision Support System for Agrotechnology Transfer, Version 3*; University of Hawaii Press: Honolulu, HI, USA, 1994.
50. Arnold, J.G.; Srinivasan, R.; Muttiah, R.S.; Williams, J.R. Large area hydrological modeling and assessment Part 1: Model development. *JAWRA J. Am. Water Resour. Assoc.* **1998**, *34*, 73–89. [CrossRef]
51. Food and Agriculture Organization of the United Nations (FAO). *CROPWAT: A Computer Program for Irrigation Planning and Management*; Food and Agriculture Organization of the United Nations: Rome, Italy, 1992.
52. Keating, B.A.; Carberry, P.S.; Hammer, G.L.; Probert, M.E.; Robertson, M.J.; Holzworth, D.; Huth, N.I.; Hargreaves, J.N.G.; Meinke, H.; Hochman, Z.; et al. An overview of APSIM, a model designed for farming systems simulation. *Eur. J. Agron.* **2003**, *18*, 267–288. [CrossRef]
53. Jones, J.W.; Hoogenboom, G.; Porter, C.H.; Boote, K.J.; Batchelor, W.D.; Hunt, L.A.; Wilkens, P.W.; Singh, U.; Gijsman, A.J.; Ritchie, J.T. The DSSAT cropping system model. *Eur. J. Agron.* **2003**, *18*, 235–265. [CrossRef]

54. Williams, J.R.; Jones, C.A.; Kiniry, J.R.; Spanel, D.A. The Epic Crop Growth-Model. *Trans. ASAE* **1989**, *32*, 497–511. [CrossRef]
55. Brisson, N.; Gary, C.; Justes, E.; Roche, R.; Mary, B.; Ripoche, D.; Zimmer, D.; Sierra, J.; Bertuzzi, P.; Burger, P.; et al. An overview of the crop model STICS. *Eur. J. Agron.* **2008**, *18*, 309–332. [CrossRef]
56. Bondeau, A.; Smith, P.C.; Zaehle, S.; Schaphoff, S.; Lucht, W.; Cramer, W.; Gerten, D.; Lotze-Campen, H.; Muller, C.; Reichstein, M.; et al. Modelling the role of agriculture for the 20th century global terrestrial carbon balance. *Glob. Chang. Biol.* **2007**, *13*, 679–706. [CrossRef]
57. Abbott, M.B.; Bathurst, J.C.; Cunge, J.A.; O'Connell, P.E.; Rasmussen, J. An introduction to the European Hydrological System—Systeme Hydrologique Europeen, "SHE", 1: History and philosophy of a physically-based, distributed modelling system. *J. Hydrol.* **1986**, *87*, 45–59. [CrossRef]
58. Renaud-Gentié, C.; Dijkman, T.J.; Bjørn, A.; Birkved, M. Pesticide emission modelling and freshwater ecotoxicity assessment for Grapevine LCA: Adaptation of PestLCI 2.0 to viticulture. *Int. J. Life Cycle Assess.* **2015**, *20*, 1528–1543. [CrossRef]
59. Tendall, D.M.; Gaillard, G. Environmental consequences of adaptation to climate change in Swiss agriculture: An analysis at farm level. *Agric. Syst.* **2015**, *132*, 40–51. [CrossRef]
60. Schaap, B.F.; Blom-Zandstra, M.; Hermans, C.M.L.; Meerburg, B.G.; Verhagen, J. Impact changes of climatic extremes on arable farming in the north of the Netherlands. *Reg. Environ. Chang.* **2011**, *11*, 731–741. [CrossRef]
61. Audsley, E.; Trnka, M.; Sabaté, S.; Maspons, J.; Sanchez, A.; Sandars, D.; Balek, J.; Pearn, K. Interactively modelling land profitability to estimate European agricultural and forest land use under future scenarios of climate, socio-economics and adaptation. *Clim. Chang.* **2014**, *128*, 215–227. [CrossRef]
62. Berry, H.L.; Hogan, A.; Ng, S.P.; Parkinson, A. Farmer health and adaptive capacity in the face of climate change and variability. Part 1: Health as a contributor to adaptive capacity and as an outcome from pressures coping with climate related adversities. *Int. J. Environ. Res. Public Health* **2011**, *8*, 4039–4054. [CrossRef] [PubMed]
63. Yegbemey, R.N.; Yabi, J.A.; Aïhounton, G.B.; Paraïso, A. Simultaneous modelling of the perception of and adaptation to climate change: The case of the maize producers in northern Benin. *Cah. Agric.* **2014**, *23*, 177–187.
64. Vermeulen, S.J.; Challinor, A.; Thornton, P.K.; Campbell, B.M.; Eriyagama, N.; Vervoort, J.M.; Kinyangi, J.; Jarvis, A.; Läderach, P.; Ramírez Villegas, J.; et al. Addressing uncertainty in adaptation planning for agriculture. *Proc. Natl. Acad. Sci. USA* **2013**, *110*, 8357–8362. [CrossRef] [PubMed]
65. Alig, R.; Latta, G.; Adams, D.; McCarl, B. Mitigating greenhouse gases: The importance of land base interactions between forests, agriculture, and residential development in the face of changes in bioenergy and carbon prices. *For. Policy Econ.* **2010**, *12*, 67–75. [CrossRef]
66. Castelletti, A.; Lotov, A.V.; Soncini-Sessa, R. Visualization-based multi-objective improvement of environmental decision-making using linearization of response surfaces. *Environ. Model. Softw.* **2010**, *25*, 1552–1564. [CrossRef]
67. Hadka, D.; Herman, J.; Reed, P.; Keller, K. An open source framework for many-objective robust decision making. *Environ. Model. Softw.* **2015**, *74*, 114–129. [CrossRef]
68. Lautenbach, S.; Volk, M.; Strauch, M.; Whittaker, G.; Seppelt, R. Optimization-based trade-off analysis of biodiesel crop production for managing an agricultural catchment. *Environ. Model. Softw.* **2013**, *48*, 98–112. [CrossRef]
69. Randhir, T.O.; Lee, J.G.; Engel, B. Multiple criteria dynamic spatial optimization to manage water quality on a watershed scale. *Trans. ASAE* **2000**, *43*, 291–299. [CrossRef]
70. Maier, H.R.; Kapelan, Z.; Kasprzyk, J.; Kollat, J.; Matott, L.S.; Cunha, M.C.; Dandy, G.C.; Gibbs, M.S.; Keedwell, E.; Marchi, A.; et al. Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions. *Environ. Model. Softw.* **2014**, *62*, 271–299. [CrossRef]
71. Wu, W.; Maier, H.R.; Dandy, G.C.; Leonard, R.; Bellette, K.; Cuddy, S.; Maheepala, S. Including stakeholder input in formulating and solving real-world optimisation problems: Generic framework and case study. *Environ. Model. Softw.* **2016**, *79*, 197–213. [CrossRef]

72. Lynam, T.; Landgridge, J.; Langston, A.; Maru, Y.T. A Bayesian network approach to investigating climate change and commodity price change impacts on human well-being: A case study of employment from Queensland, Australia. In *Climate Adaptation Futures*; Palutikof, J., Boulter, S.L., Ash, A.J., Smith, M.S., Parry, M., Waschka, M., Guitart, D., Eds.; Wiley & Sons: Chichester, UK, 2013; pp. 322–331.
73. Webber, H.; Gaiser, T.; Ewert, F. What role can crop models play in supporting climate change adaptation decisions to enhance food security in Sub-Saharan Africa? *Agric. Syst.* **2014**, *127*, 161–177. [CrossRef]
74. De Nijs, P.J.; Berry, N.J.; Wells, G.J.; Reay, D.S. Quantification of biophysical adaptation benefits from Climate-Smart Agriculture using a Bayesian Belief Network. *Sci. Rep.* **2014**, *4*. [CrossRef] [PubMed]
75. Lieske, D.J. Coping with climate change: The role of spatial decision support tools in facilitating community adaptation. *Environ. Model. Softw.* **2015**, *68*, 98–109. [CrossRef]
76. Romsdahl, R.J. Decision support for climate change adaptation planning in the US: Why it needs a coordinated internet-based practitioners' network. *Clim. Chang.* **2011**, *106*, 507–536. [CrossRef]